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Review

Wetland carbon models: Applications for wetland carbon commercialization

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ABSTRACT

Processed-based biogeochemical mathematical models are powerful tools that are increasingly being used to estimate potential carbon sequestration and greenhouse gas (GHG) impacts of management at a landscape level. These models can simulate some or all of the processes responsible for carbon sequestration and GHG emissions, which can relieve some of the burdensome in-situ monitoring requirements that make many blue carbon projects cost-prohibitive. Here we selectively review five publicly available and widely used biogeochemical models (MEM, PEPRMT, DNDC, DayCent and FVS) including their current applications and limitations towards blue carbon project development. Of the five models, only the DNDC model can be applied to fully account for net sequestration as applicable to blue carbon offset methodologies. With further development, the DayCent and the combined MEM/PEPRMT models may prove to be applicable. Successful application of such models will address one of the biggest barriers to landscape-scale blue carbon project development.

1. Introduction

Wetland restoration and conservation provide a wealth of benefits such as storm surge reduction, fish and wildlife habitat, water quality improvement, recreation, job creation, and carbon sequestration (Batker et al., 2010; Jenkins et al., 2010). One of the largest challenges to wetland management is finding sufficient financing for coastal restoration and conservation that is on the scale that most stakeholders agree is needed. Carbon sequestration refers to the removal of atmospheric carbon, in this case by plants (photosynthesis) or other storage mechanisms (i.e., soils), which can mitigate greenhouse gasses released as a result of changes in land use and the burning of fossil fuels (Lal 2004; Euliss et al., 2006; Kayranli et al., 2010). Traditionally, the carbon sequestered in vegetated coastal ecosystems, specifically mangrove forests, seagrass beds, and salt marshes, has been termed 'blue carbon' (Nellemann et al., 2009; Mcleod et al., 2011), although the authors believe this definition should be expanded to include tidally influenced cypress-tupelo forests and freshwater marshes (Lane et al., 2017; Edwards et al., 2019). Wetland restoration is an effective climate change mitigation strategy because it enhances carbon sequestration and avoids carbon releases over time that would occur in the absence of restoration activities (Pendleton et al., 2012; Lane et al., 2016; Sapkota and White 2019). Because wetlands sequester large amounts of carbon in soils and plants, the growing carbon market provides a potential funding source to support restoration and conservation of these valuable ecosystems (Murray et al., 2011). However, burdensome in-situ monitoring and large monitoring uncertainties associated with measurement constraints may add to the already high cost of blue carbon projects, potentially making them cost-prohibitive.

The foundational principle underpinning high-quality offset projects is called additionality. Additionality maintains that an offset credit is granted only to the extent that the associated amount of emissions reduced or sequestered within the project boundary is additional to that which would occur without the project, or under business-as-usual conditions (Mack et al. 2015; Murray et al. 2007; Murray et al., 2011). This requires estimation of the carbon sequestered and GHG emissions under the "baseline scenario" (i.e., business-as-usual) and the "project scenario" (i.e., the restoration activity), with the net difference being

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counted towards carbon offsets (Bridgham et al. 2006).

Processed-based biogeochemical mathematical models are powerful tools that are increasingly being used to estimate potential carbon sequestration and greenhouse gas (GHG) impacts of management at a landscape level (e.g., Alizad et al., 2016; Baustian et al., 2018; Gilhespy et al. 2004; Schile et al. 2004; Zhang et al., 2002). These models can simulate some or all of the processes responsible for carbon sequestration and GHG emissions. Models can also be used to compare alternative management scenarios intended to reduce emissions, as well as address many of the challenges of blue carbon project development. The appropriate wetland carbon model would significantly reduce project costs by facilitating the practice of "MRV", which consists of monitoring (M), reporting (R), and verification (V) to catalyze landscape-scale blue carbon project development that provide multiple co-benefits to society. Conventional MRV can be costly and complicated to implement. Assessments, auditing and registering tend to be labor-intensive, time consuming and require extensive in-situ monitoring to meet carbon market uncertainty requirements.

Most land use change (LUC) project types require the use of a process-based biogeochemical model that can predict the greenhouse gas fluxes from living systems (De Rosa et al. 2016). These models do not usually account for hydrologic features, meaning that a project developer would need to utilize multiple models, necessitating a broader expertise than most project developers possess. As noted in the USDA *Quantifying Greenhouse Gas Fluxes in Agriculture and Forestry: Methods for Entity-Scale Inventory*, Section 4–21 states "Improving modeling capabilities that integrate surrounding areas with the wetlands that receive surface and subsurface drainage waters will allow for modeling the flows of nutrients and organic matter into wetlands and subsequent losses to other wetlands beyond the entity's operation. This type of assessment framework is used in several established spatially-explicit hydrologic models; the need is to integrate the biogeochemistry. Linked models can be used at present; but development of a functionally-integrated system is needed to support broad-based applications." At this time, no adequate publicly available biogeochemical model for the Mississippi Delta region exists, leaving project developers with no other option than to conduct extensive field measurements.

Overwhelming measurement and monitoring criteria may stifle any financial benefits that carbon credits may deliver (Robertson et al., 2004). Agriculture, forestry and other land-use (AFOLU) projects use a combination of modeled and measured data to quantify the emission reductions associated with LUC (De Rosa et al. 2016). Forest carbon projects can rely on robust data sets to inform allometric equations that are universally agreed upon (Pilli et al., 2006). Agricultural carbon projects utilize publicly available datasets that require costly model validation and geographic calibration, which is just coming to the forefront of offset project development. Wetlands offset projects, however, do not have a single sufficient model that is universally accepted, making extensive in-situ monitoring necessary, which can be cost-prohibitive.

Monitoring and measuring requirements for blue carbon projects may have made the possibility of scaling this project type unfeasible. To address this barrier, a process-based biogeochemical model is needed that can simulate the GHG fluxes and net sequestration for wetland restoration activities. Such a model would need to be tested at multiple sites with differing soils, climates, and land-use and management scenarios to establish efficacy, and then once deemed reliable used to simulate sequestration and emissions, and derive stock change factors (Smith et al. 2020). The development and application of such a model would reduce: 1) the uncertainty associated with measurement constraints, 2) the cost of monitoring, and 3) safety issues associated with on-the-ground monitoring of inaccessible areas. Deterministic or process modeling provides the ability to simulate the physical, chemical and biological processes that comprise the exchange of greenhouse gasses between the atmosphere, vegetation and soil (Lloyd et al., 2013). In wetlands, these models need to be extended to include microbial activity processes responsible for CH_4 production and oxidation, water table depth, seasonal changes in wetland expanse, as well as lateral exchanges of carbon (C) and nitrogen (N) between wetland and surrounding areas.

This paper serves as a review of five publicly available and widely used ecosystem models that show promise towards being applied to blue carbon projects including their current applications and limitations. The ultimate goal is to provide guidance for future spatial biogeochemical model development or refinement that can be used to estimate various carbon pools or fluxes (i.e., soil organic carbon, biomass, greenhouse gasses) from fresh, brackish and saltwater wetlands in the Mississippi delta for various baseline and restoration scenarios. This will address one of the biggest barriers to landscape-scale blue carbon project development in the Mississippi delta.

2. Model analysis

Here we discuss five publicly available process-based models currently being used, or show promise to be applied, to estimate net carbon sequestration: the MEM (Marsh Equilibrium Model), the PEPRMT (Peatland Ecosystem Photosynthesis, Respiration, and Methane Transport) model, the DNDC (Denitrification-Decomposition) model, the DayCent model, and the FVS (Forest Vegetation Simulator) model (Table 1). The Marsh Equilibrium Model (MEM) predicts how aboveground biomass and surface elevation of salt marshes respond to projected sea-level rise. The PEPRMT model estimates net ecosystem exchange of CO_2 and CH_4. The PEPRMT model is currently being merged with the MEM (MEM/PEPRMT) to account for accretion and better account for net sequestration, but is only designed for non-forested emergent wetlands (salt to fresh) and cannot be applied to forested systems such as mangroves and cypress. The DNDC model is a process-based model simulating C and N dynamics in forested and emergent wetland ecosystems, including mangrove forests (Dai et al., 2018a;b), but has not been applied to cypress forests and can have high levels of uncertainty under some conditions (Gilhespy et al., 2014). The DayCent model is a daily time step version of the Century biogeochemical model, and simulates fluxes of C and N between the atmosphere, vegetation, and soil. The FVS model projects the growth and development of forest stands with application of various silvicultural treatments.

The time step used by empirical models has implications for data collection and input. A daily time step is used by the PEPRMT, DNDC, and DayCent models (Table 1), which allows for the direct use of field observations of greenhouse gas emissions to calibrate and evaluate the model, and to answer questions about climatic change and management practices (Zhang et al., 2002). The MEM model uses an annual timestep, which correlates to field measurements of emergent biomass and surface elevation changes, which are normally measured once per year. The FVS model has the longest time step of 5 or 10 years for tree growth, however, this period of time correlates with the five-year monitoring interval mandated by most carbon registries, such as the American Carbon Registry (ACR). Below are more detailed descriptions of the models.

2.1. MEM (Marsh equilibrium model)

The Marsh Equilibrium Model (MEM) is a one-dimensional mechanistic model with and annual time step that incorporates feedbacks of organic and inorganic inputs to project accretion and wetland surface elevations under varying sea-level rise and sediment availability scenarios (FitzGerald and Hughes, 2021). Combining a simple spreadsheet-based model interface with a fast-processing time, the MEM is accessible for a broad array of end-users. Additionally, the MEM can be run using upland elevations that are not currently inundated to examine the timing and extent of marsh migration with a given rate of sea level rise (Schile et al., 2014). Physical inputs for the model include the initial rate of sea level rise, mean sea level, mean higher high water (MHHW), suspended sediment concentration, and starting marsh elevation (Fig. 1). Biotic inputs include the minimum and maximum

Table 1
Models included in this analysis, model outputs, wetland types, data gaps, skill level necessary to run the model, and time step used by the model.

Name	Model Outputs	Wetland Type	Data Gaps	Skill Level Necessary	Time Step
MEM	AGB, BGB, SOC Surface Elev.	Salt Marshes & Mangroves	No GHGs	Easy	Annual
PEPRMT	CO_2 & CH_4	Freshwater Peat (CA)	No AGB, No SOC, No N_2O	Difficult	daily
MEM/PEPRMT	AGB, BGB, Surface Elev., CO_2 & CH_4	Non-forested Emergent	No N_2O	Difficult	annual/daily
DNDC	AGB, BGB, SOC, CO_2, CH_4, N_2O, NO, N_2 NH_3	Forested & Emergent	Currently no cypress application	Difficult	daily
DayCent	AGB, BGB, SOC CO_2, CH_4, N_2O, NO_x	Rice Paddy	Currently not applicable to wetlands	Moderate	daily
FVS	AGB BGB	Forested	No SOC, No GHGs	Moderate	5 or 10 years

Aboveground biomass (AGB), belowground biomass (BGB), soil organic carbon (SOC), greenhouse gasses (GHGs).

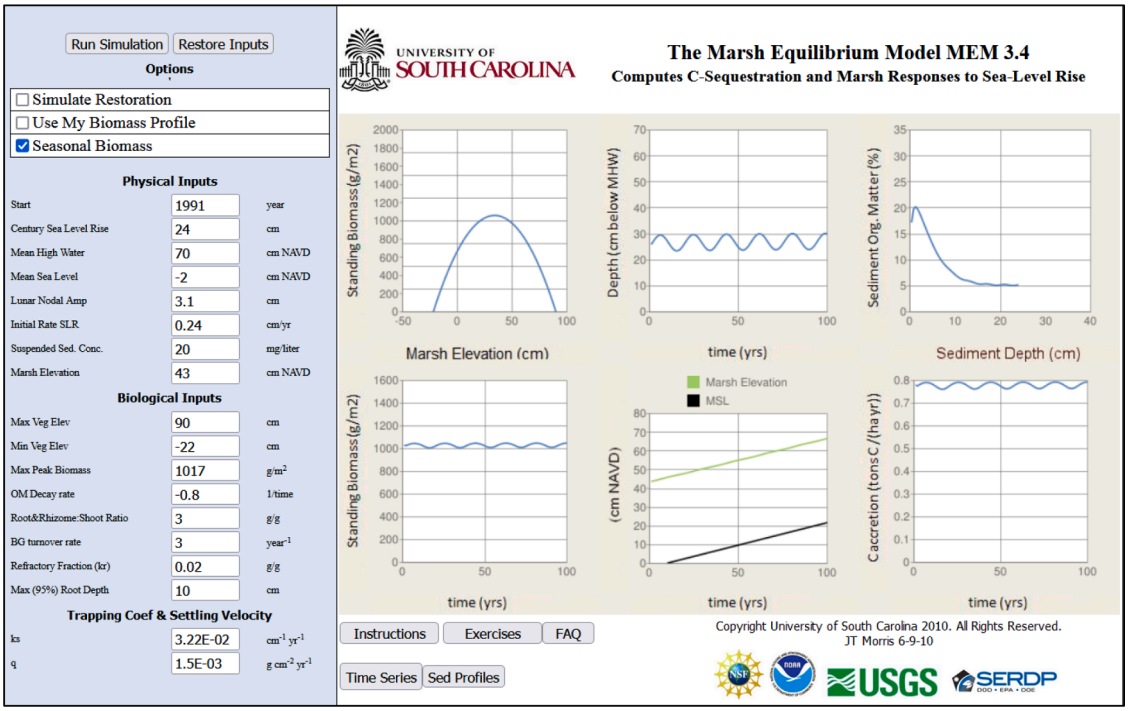

Fig. 1. Screenshot of the MEM available online.

elevation for marsh vegetation, the peak aboveground biomass and the elevation at which it occurs, root to shoot ratio, organic matter decay rate, percent of refractory carbon, belowground turnover rate, and maximum rooting depth of 95% of the roots. Byrd et al. (2016) used values derived from remote sensing to provide inputs of suspended sediment concentration and aboveground peak biomass.

The model assumes that plant productivity is constrained by upper and lower elevation limits and there is an optimum elevation for growth within the tidal frame (Morris et al., 2002). MEM relies on the idea that: 1) marshes either increase or decrease biomass production in relation to changes in sea-level, 2) a combination of biomass and inundation time influences the settling of suspended inorganic sediment and 3) these two factors influence changes in marsh elevation (Morris et al., 2002). Plant productivity varies with relative elevation in a parabolic response across a limited range of the tidal frame, with peak productivity occurring at an optimal mid-elevation point (Morris et al., 2013; 2016). An increase in the rate of SLR may cross a threshold whereby relative elevation becomes sub-optimal for growth and accretion rates are insufficient to maintain elevation, leading to elevation loss (Morris et al., 2002).

Since the MEM only forecasts changes in elevation at a single point, it is often coupled with another spatially-explicit landscape scale model in order to accurately capture the dynamics of a marsh system. For example, Schile et al. (2014) coupled the MEM with a high spatial resolution LiDAR-based digital elevation model to estimate changes in marsh elevation and extent, including upland migration, under a variety of sea level rise and suspended sediment concentration scenarios. Several researchers have coupled the MEM with two-dimensional hydrodynamic models to forecast the fate of coastal wetlands in response to sea level rise (Mudd et al., 2004; Hagen et al., 2013; Alizad et al., 2016), while D'Alpaos et al. (2006) coupled the MEM to a hydrodynamic model to investigate the geomorphology of tidal channels.

The strengths of the MEM model include the ability to forecast saltmarsh productivity and relative elevation, and decomposition rates can easily be converted to CO_2. The model was recently revised to include mangroves, and allows for mangrove growth to maturity, episodic storm inputs of sediment, or thin layer sediment applications (TLP). Therefore, this model can be used to quantify carbon sequestration in saltmarshes and mangroves and in some instances prevented loss. For example, the user can by trial and error optimize the periodic application of sediment by TLP to maximize carbon sequestration and resilience to sea-level rise. The model makes a distinction between sustained carbon sequestration, defined as the annual increase in soil carbon standing stock, and sequestered carbon–the actual standing stock of organic matter or organic carbon in soils. Standing stock includes

living and labile organic matter. The live standing stock in a salt marsh or mature mangrove forest is a constant and does not add to carbon sequestration, and labile organic matter will decay. Decaying organic matter does not contribute to sequestration, but it is part of the standing stock. Sustained carbon sequestration is defined as the annual input to soil of refractory or stable organic matter, which is a function of the turnover of roots and rhizomes, and the lignin concentration in live organic matter. If the salinity is input the model can also estimate CH_4 (as in Poffenbarger et al. 2011; Jim Morris personal communication).

In general, this model the ability to fully account for all GHGs (i.e., N_2O and CH_4). A weakness of MEM is that it does not allow for net erosion. Erosion of the marsh platform is not explicitly included in the model. Neither can it simulate edge erosion. The model can simulate a drowning marsh overwhelmed by rising sea level, but the model marsh cannot drown by erosion in the absence of rising water level. Furthermore, the publicly available model version does not allow for temporal changes in suspended sediment concentration, but scenarios such as that can be coded by the developer.

The MEM interface is relatively simple and does not require an extensive background to apply the model. It was designed to be parsimonious. One aspect of carbon project development is determining the "permanence" of a restoration activity (i.e., the risk that a carbon sink having delivered emissions reductions may deteriorate or become depleted over the long term). Given adequate elevation data, this model is ideal for determining the sustainability of a given wetland ecosystem, including the period of time before submergence and when deterioration of the carbon sink begins to take place. However, detailed elevation data are rare and may be expensive to acquire. An executable version of MEM with an Excel user interface is available upon request, and an older version of MEM is publicly available online at: http://129.252.139.226/model/marsh/mem2.asp

2.2. PEPRMT (Peatland ecosystem photosynthesis, respiration, and methane transport)

The Peatland Ecosystem Photosynthesis, Respiration, and Methane Transport (PEPRMT, pronounced "peppermint") model, is a process-based biogeochemical model that predicts CO_2 and CH_4 exchange in peat soil freshwater wetlands and rice paddies using a daily time step (Fertitta-Roberts et al., 2019). The model makes the assumption that N_2O emissions are insignificant due to fully saturated soils emitting N_2 (Patty Oikawa personal communication). It is designed to simulate the complex biogeochemistry of peatlands using few inputs and simple model structure (Fig. 2). Originally developed for the Sacramento-San Joaquin Delta, California, it is cited in The Restoration of California and Coastal Wetlands methodology by the American Carbon Registry (ACR), and is being modified to be used in tidal marshes (Patty Oikawa personal communication). It can estimate emissions from both natural and restored wetlands. The biogeochemistry and greenhouse gas flux dynamics of restored wetlands are very different compared to natural undisturbed wetlands since large amounts of soil may be moved in the restoration process, likely exposing previously inaccessible carbon, leading to high greenhouse gas fluxes (Oikawa et al., 2017).

The model requires leaf area index (LAI), meteorological data, initial soil organic carbon content (SOC), and water table height. Carbon flux dynamics in the PEPRMT model are sensitive to water table height, substrate availability, leaf area, temperature, and light (Fertitta 2017). The model simulates three carbon (C) pools in order to predict ecosystem CO_2 and CH_4 production: recently fixed labile C, C stored in plant biomass, and older more recalcitrant soil organic carbon (SOC; Oikawa et al., 2017). The model simulates the top meter of soil and tracks the water level in the soil horizon, which governs CO_2 and CH_4 emissions. Whenever the water table falls below the soil surface, CH_4 production is strongly inhibited (Fertitta-Roberts et al., 2019).

The PEPRMT model is ideal for use in carbon market systems that calculate CO_2 and CH_4 exchange on an annual basis using measured inputs, but the model is not suitable for estimating long-term C storage in soils. In order to predict long-term C storage, the model would require additional data such as SOC measurements and soil C turnover times in order to constrain model parameters that predict soil C pools over long time scales (Oikawa et al., 2017). Net CO_2 exchange is calculated as the difference between photosynthesis and respiration, meaning that the net uptake of CO_2 by the system is either being stored in biomass or lost laterally. This would include below- and aboveground biomass, but would not differentiate how the carbon is distributed across these two pools. The PEPRMT model also provides rigorous estimates of uncertainty in CO2 and CH4 fluxes as it is parameterized using a model-data fusion approach with high resolution ecosystem scale GHG flux measurements (Oikawa et al., 2017). Highly constrained estimates of uncertainty are helpful when participating in carbon markets, as unconstrained uncertainty can lead to conservative estimates of uncertainty with associated credit deductions.

This model was successfully applied to the first wetland restoration carbon offset project in the United States located within the Sacramento-San Joaquin Delta that converted agricultural lands back to wetlands (i.e., flooding lands previously used for agriculture). This project reduces GHG emissions by; (1) halting the oxidation of organic soils due to farming that results in the release of CO_2 and CH_4, and (2) stopping CH_4 and N_2O emission from fertilization and grazing animals existing under the baseline scenario. The methodology developed for this project specifically uses the PEPRMT model to estimate CO_2 and CH_4 emissions.[1]

The PEPRMT model is publicly available at https:// github.com/pattyoikawa/PEPRMT.git. However, currently the model requires professional coding skills which is beyond the expertise of most project developers. Other limitations of the model include the inability to quantify aboveground biomass, soil organic carbon, and N_2O.

The PEPRMT model is currently being merged with the MEM to account for accretion and better account for net sequestration (personal communication with Patty Oikawa). The merged MEM/PEPRMT model uses MEM to simulate soil organic carbon and accretion and relies on soil core data from the Coastal Carbon Research Coordination Network (CCRCN) for model validation[2];). The MEM/PEPRMT model is being designed for non-forested wetland systems ranging from fresh to saltwater. Currently there are two sites in Louisiana that this model is being applied. One with the assistance of the United States Geological Service (USGS) in a floating freshwater tidal marsh influenced by the Davis Pond river diversion and the other site is at a brackish saltmarsh. The model does not measure N_2O and assumes that this source is negligible, which may require further scientific justification by the carbon standard dependent upon the specific methodology the model would be applied to.

The MEM/PEPRMT model validation is believed to be applicable to non-forested marshes throughout Louisiana and should be available in the near future. Currently, this model is not publicly available but there is an intent to make this model public. It is currently unknown the level of expertise that would be required to operate the model. The main gap of this model is that it cannot be applied to forested systems such as mangroves and bald cypress. However, this model shows promise to be applied in non-forested wetland systems.

2.3. DNDC (DeNitrification-DeComposition) model

The DNDC (DeNitrification DeComposition) model was first described by Li et al. (1992) as a process-orientated biogeochemical model for simulating N_2O and SOC change from agricultural soils in the U.S (Gilhespy et al., 2014). The DNDC model has incorporated a suite of biogeochemical processes (e.g., decomposition, fermentation, ammonia

[1] https://americancarbonregistry.org/carbon-accounting/standards-methodologies/restoration-of-california-deltaic-and-coastal-wetlands

[2] https://serc.si.edu/coastalCarbon

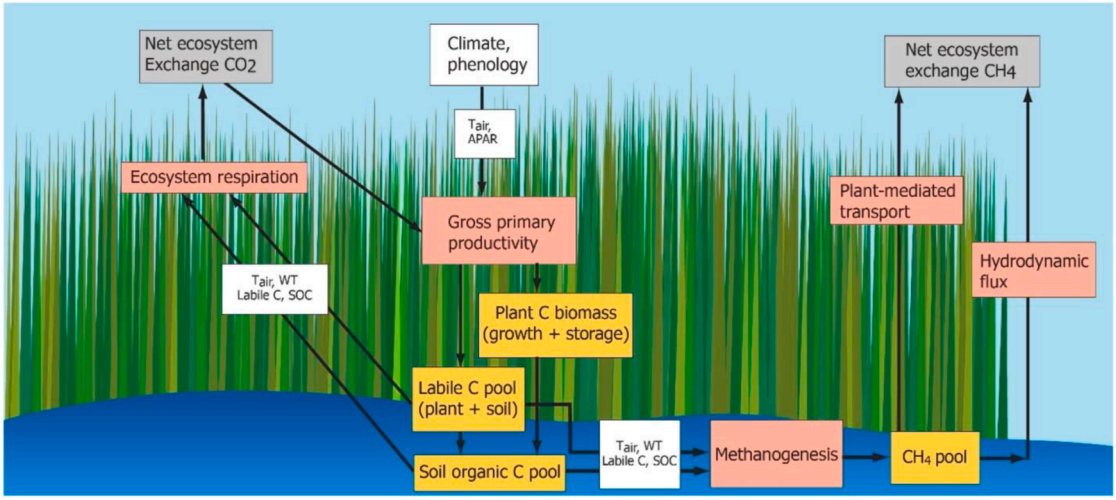

Fig. 2. The conceptual basis for the PEPRMT model. Model inputs and drivers—air temperature (Tair), absorbed photosynthetically active radiation (APAR), water table height (WT), labile soil C, and soil organic carbon (SOC)—are shown in white boxes. Model outputs are shown in gray boxes. Processes and pools modeled within PEPRMT are shown in pink and orange boxes, respectively (from Oikawa et al., 2017).

volatilization, nitrification, denitrification), as influenced by the soil environment, to predict C and N turnover in agricultural soils. The model can run from a year to several hundred years with a primary time step of 1 day. During the past 30 years the original DNDC model has been modified and adapted to simulate other ecosystems, including wetlands.

The DNDC model was developed for wetlands by integrating two existing models, namely, PnET-N-DNDC and FLATWOODS (Gilhespy et al., 2014), to predict CO_2 and CH_4 emissions from wetland ecosystems (Zhang et al., 2002). Several new functions were developed for the DNDC model to represent the unique features of wetland ecosystems, such as water table dynamics, growth of mosses and herbaceous plants, and soil biogeochemical processes under anaerobic conditions (Zhang et al., 2002). Forested wetlands can be modeled using the Forest-DNDC model, which simulates forest biomass dynamics by tracking the growth of upperstory, understory (e.g., bushes or shrubs), and ground-level vegetation (e.g., moss, herbaceous plants, or lichens) based on their competition for light, water, and N (Li et al., 2004).

Model inputs primarily include initial conditions (e.g., plant biomass, soil physical and chemical properties, water table position),

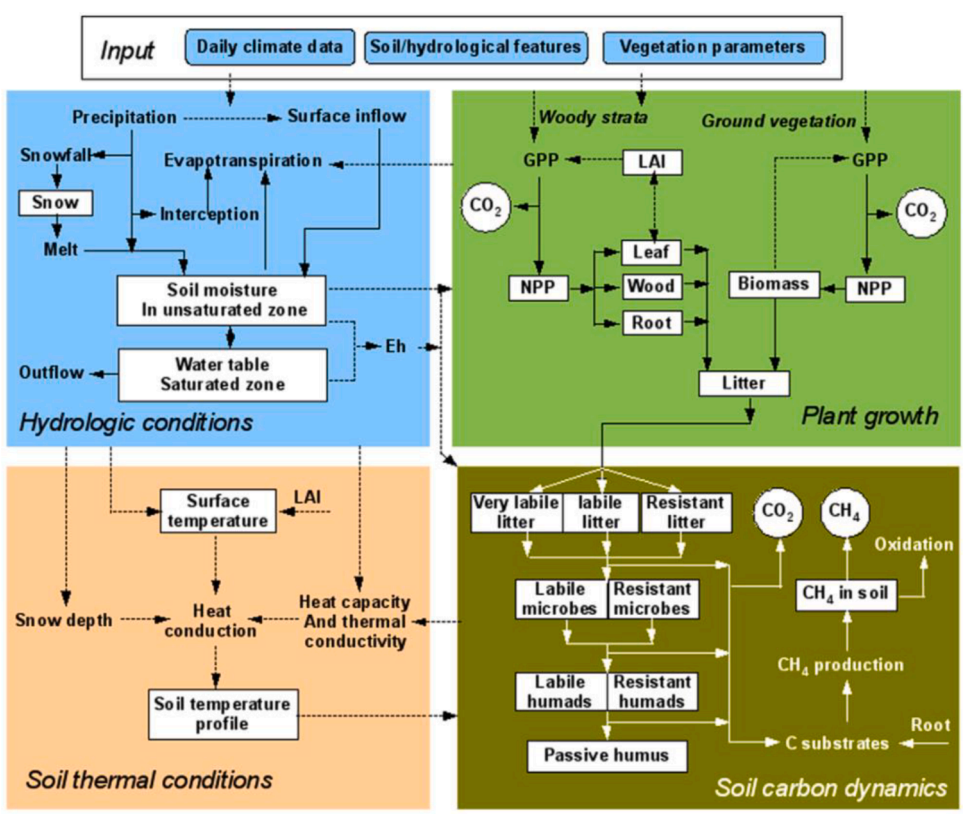

Fig. 3. The conceptual structure of the DNDC model for wetlands (from Lloyd et al., 2013).

hydrological parameters (e.g., lateral inflow/outflow parameters), vegetation phenological and physiological parameters (e.g., maximum photosynthesis rate and its partitioning to shoot and root, respiration rate), and climate drivers (e.g., daily maximum and minimum temperature, precipitation, solar radiation). Model outputs primarily include C pools and fluxes (e.g., C in plants and soil, photosynthesis, plant respiration, soil decomposition, CH_4 emissions, and net ecosystem productivity), N pools and fluxes (e.g., N in plants and soil, and emissions of N gasses), and soil thermal/hydrological conditions (e.g., soil moisture, water table position, water fluxes, soil temperature profile).

The DNDC model consists of four interacting sub-models that simulate water table dynamics, soil temperature, plant growth of wetland species and the anaerobic biogeochemical processes in wetlands (Fig. 3; Zhang et al., 2002). Li et al. (2004) modified the 'anaerobic balloon' concept to integrate the Nernst and Michaelis–Menten equations, enabling the modeling of soils where aerobic and anaerobic microsites exist simultaneously, and the prediction of both nitrification and denitrification in the soil at the same time. In recent years, the model has been further improved to simulate C and N dynamics in northern peatlands (Zhang et al., 2012; Deng et al., 2014, 2015, 2017) and mangrove forests (Dai et al., 2018a,b) by integrating new processes to represent these systems. The primary strength of the DNDC model is its inclusion of most of the carbon pools of interest, however, it currently cannot model the growth of cypress trees, and the model itself is rather complicated, requiring expertise and computational skills.

2.4. DayCent

The DayCent model is a version of the Century ecosystem model but with a daily time step, and is used to simulate ecosystem responses to changes in climate and agricultural management practices in crop, grassland, forest and savanna ecosystems (Necpálová et al., 2015). The DayCent model was developed to permit more realistic estimates of greenhouse gas exchange between the soil and the atmosphere (Parton et al., 1998, 2001). It has been used to estimate N_2O emissions from agricultural soils for the US National Greenhouse Gas Inventory (Olander and Haugen-Kozyra 2011; USEPA 2021), and the USDA relies on the Century and Daycent models to estimate direct and indirect GHG emissions for major croplands in the United States (USGS 2010). DayCent consists of sub-models for soil water content and temperature by layer, plant production and allocation of net primary production (NPP), decomposition of litter and soil organic matter (SOM), as well as carbon, nitrogen, phosphorus and sulfur cycling, N gas emissions from nitrification and denitrification, and CH_4 formation from unsaturated soils (Fig. 4). Methane emissions from saturated rice paddy soils have also been added (Cheng et al. 2013), and work is currently being done to use the DayCent to model natural wetlands systems (personal communication Ellen Herbert, Ducks Unlimited). Ducks Unlimited and its partners are collecting data on carbon stocks of wetland soils as well as vegetation carbon levels at 250 wetland sites across a 15-state area in the central united states. The primary strengths of the DayCent model are its inclusion of all of the carbon pools of interest and relative ease of use compared to the DNDC and PEPRMT models. The DayCent model can be accessed by request through: century@colostate.edu.

Daily maximum/minimum temperature and precipitation, timing and description of management events (e.g., fertilization, tillage, harvest), soil texture, vegetation productivity and root:shoot ratios, and land cover/use data are needed as model inputs. The plant growth sub-model simulates plant productivity as a function of genetic potential, phenology, nutrient availability, soil water and temperature, and solar radiation (Necpálová et al., 2015). Nutrient supply is a function of soil organic matter (SOM) decomposition and external nutrient additions (Del Grosso et al. 2005). SOM is simulated in the top 20 cm soil layer as a sum of dead plant matter and three SOM pools divided on the basis of decomposition rates, which are controlled by substrate availability, substrate quality (lignin content, C/N ratio), soil moisture/oxygen concentrations, temperature and pH (Del Grosso et al. 2008a; Malone et al., 2015). The SOM pool is divided into active (0.5–1.0 yr), slow (10–50 yr), and passive (1000–5000 yr) pools based on residence time (Weiler et al., 2018).

The methanogenesis sub-module simulates CH_4 production based on carbon substrate supply for methanogens, which is derived from decomposition of SOM and root rhizodeposition, and the impact of environmental variables. Parameters controlling methanogenesis include soil texture, soil pH, redox potential (Eh), soil temperature, climate and management practices (Cheng et al. 2013). Plant-mediated emissions account for nearly 90% of CH_4 emissions from soil, while a smaller proportion of the CH_4 is emitted via ebullition, which occurs when the soil CH_4 concentration exceeds a critical state that leads to formation of bubbles (Cheng et al. 2013).

The trace gas sub-model of DayCent simulates soil N_2O and NO_x (i.e., NO and NO_2) gas emissions from nitrification and denitrification processes. The model includes legacy effects such that N added to the system one year may be taken up by vegetation and returned to the soil in organic form during that year, then remineralized and emitted as N_2O in following years (Del Grosso et al. 2005). The sub-model assumes that nitrification and denitrification both contribute to N_2O and NO_x emissions, but that NO_x emissions are due mainly to nitrification. N_2O emissions from nitrification are calculated as a function of modeled soil NH_4 concentration, water filled pore spaces (WFPS), temperature, pH, and texture, while N_2O emissions from denitrification are a function of soil nitrate concentration, WFPS, heterotrophic respiration and soil texture (Del Grosso et al. 2008a;b). NO_x emissions are calculated as a function of soil bulk density, field capacity, and WFPS that influence gas diffusivity (Parton et al., 2001).

2.5. FVS (Forest vegetation simulator)

The Forest Vegetation Simulator (FVS) is the U.S. Forest Service's nationally supported framework for forest growth and yield modeling, particularly with respect to the application of silvicultural treatments (USFS 2002, 2020). At its core, FVS is an individual-tree, distance-independent growth model; it predicts changes in tree diameter, height, crown ratio, and crown width, as well as mortality, over time (USDA Forest Service 2011). FVS evolved from a relatively focused growth and yield model, the Prognosis Model for Stand Development, and growth equations were developed for other parts of north America. Geographically specific versions of FVS are called variants. Twenty-two FVS variants have been developed for the forested areas of the United States and for part of British Columbia, Canada (Fig. 5). The 'Southern (SN)' variant, released in 2001, includes cypress and water tupelo forests. Ecological Unit Codes (EUC) of the Southern variant include categories such as Coastal Marsh and Island, Tidal Area, Gulf Coastal Lowlands, and LA Gulf Coast Marshes and Inland Bays (Appendix A of USFS 2008). The FVS software package is freely available at: http://www.fs.fed.us/fmsc/fvs/.

The FVS models individual trees with key state variables for each tree being density, species, diameter, height, crown ratio, diameter growth, and height growth (Crookston and Dixon 2005). Key variables for each sampling site include slope, aspect, elevation, density, and a measure of site potential. If these values are not provided, default values are used. A distinguishing feature of FVS is its ability to automatically calibrate internal models to reflect local deviations from the regional growth trends represented in the variant (Crookston and Dixon 2005). If three or more tree records for a species have measured heights, the model parameters of the height-diameter function for that species are adjusted. Time steps are generally between 5 and 10 years long, and the total projection is between a few years and several hundred years.

To meet increased demand for forest carbon information, a tool was developed to calculate forest carbon stocks. Two carbon reports can now be requested: the Stand Carbon Report and the Harvested Carbon Report (USDA Forest Service 2011). The Stand Carbon Report includes the

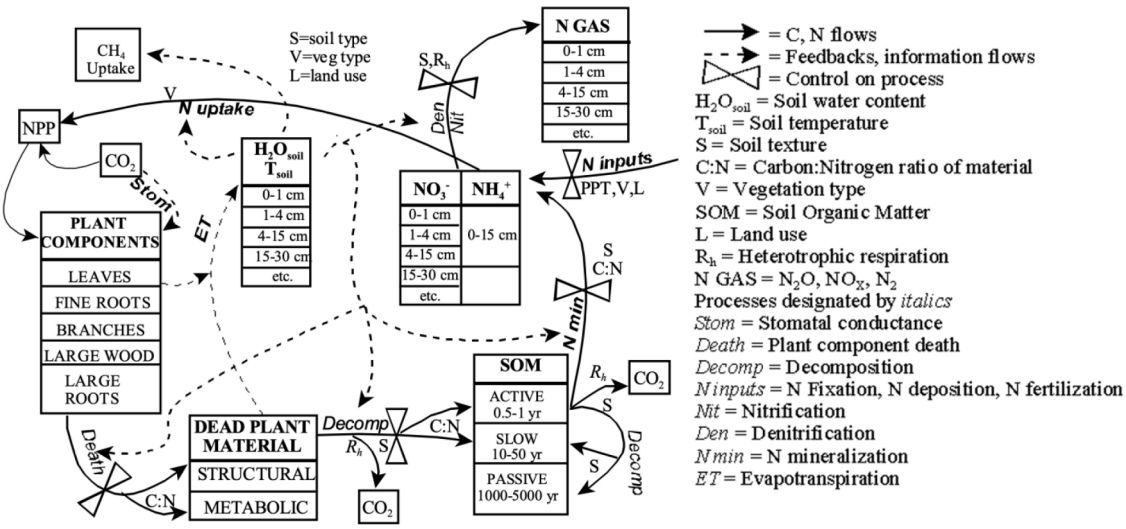

Fig. 4. Flow diagram for the DayCent ecosystem model (modified from Parton et al., 2001).

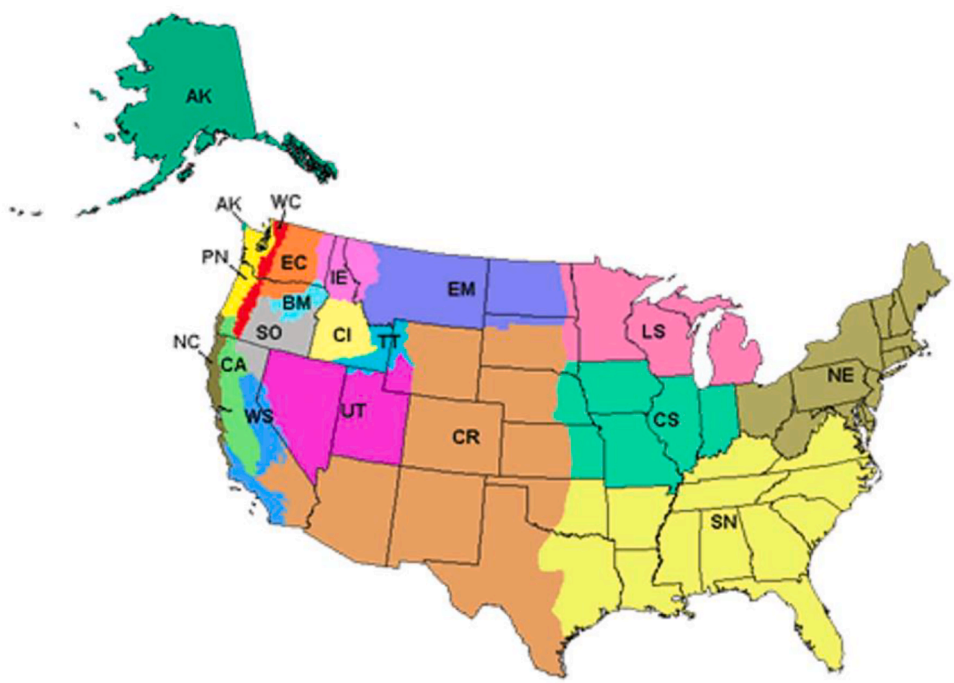

Fig. 5. Geographic variants of the Forest Vegetation Simulator.

major carbon pools as defined by the U.S. Carbon Accounting Rules and Guidelines and the IPCC Good Practice Guidance: aboveground live tree, belowground live tree (coarse roots), belowground dead tree, standing dead trees, down dead wood, forest floor, and understory (shrubs/herbs). The Harvested Carbon Report tracks the fate of carbon in harvested merchantable material, including salvaged logs. Most carbon registries require that forest carbon storage be 'additional', or above-and-beyond business-as-usual (BAU), to receive emission offsets. Using data from an appropriately designed forest inventory, managers can generate baseline carbon stock estimates by simulating the BAU management actions for a given stand, and carbon stock estimates can be made for alternative management scenarios for comparison.

A major limitation of the FVS was that it was not directly sensitive to environmental changes that influence tree growth such as increasing temperatures, changes in rainfall, and changes in atmospheric CO2, making the model insensitive to climate change (Crookston and Dixon 2005). This changed with the development of the Climate-FVS, a modification to the FVS designed to take climate change into account when predicting forest dynamics at decadal to century time scales (USDA Forest Service 2014). The Climate-FVS uses individual tree climate viability scores, which measure the likelihood that the climate at a given location and at a given point in time is consistent with the climate recorded for species' contemporary distribution, and adjusts growth and mortality accordingly. Now the biggest limitation of the FVS model is that it does not model the soil carbon pool, nor are there estimates of greenhouse gasses.

The FVS software package is freely available at: http://www.fs.fed.us/fmsc/fvs/. modeling would benefit from an experienced user, but special expertise is not necessary and there are several comprehensive Users Manuals available.

3. Discussion

3.1. Carbon model limitations

Of the five models included in this analysis, the DNDC model includes the most carbon pools of interest and is currently the only model that has potential to be applied to fully account for net sequestration as applicable to blue carbon offset methodologies. The DayCent model and the MEM/PEPRMT combined model may prove with time and development to be applicable. There are limitations and uncertainties for almost all wetland carbon models; including uncertainties in biological processes of relevant parameters (as discussed in Deng et al., 2017), and limitations in simulating landscape interactions and evaluation of regional outputs. Uncertainties associated with these limitations require associated credit deductions that can ultimately become cost-prohibitive to a project. In general, these limitations need to be addressed but are beyond the scope of carbon market applications to blue carbon projects.

The MEM is most applicable to projecting the interaction of sea level rise and wetland surface elevation to aboveground biomass in the baseline and project scenarios, but does not quantify carbon sequestration in a way that is applicable to existing methodologies. However, this model is applicable towards forecasting the impacts of sea level rise for baseline and project scenarios. The uncertainty in data inputs to coastal forecasting models such as MEM can limit prediction accuracy and as a result the usefulness of models in management and planning (Byrd et al., 2016). Consequently, accurate information on baseline conditions of tidal marshes across the modeling spatial extent is essential for generating realistic forecasts, as baseline conditions set the starting trajectory of change.

The MEM can predict above-ground biomass (AGB), and by extension below ground biomass (BGB) using a root:shoot ratio for salt marshes and mangroves, leaving a knowledge gap for freshwater forested and emergent wetlands. The PEPRMT model was developed to predict CO_2 and CH_4 from peat wetlands in California, but when combined with the MEM is applicable to all non-forested wetlands (Patty Oikawa personal communication). However, it does not account for N_2O. The DNDC model predicts greenhouse gas emissions from wetlands, though estimates of N_2O in the absence of any additional N fertilization have been questioned by some modeling experts (Gilhespy et al., 2014). The DayCent model predicts all necessary parameters, but is not yet applicable to deltaic wetlands. The Forest Vegetation Simulator (FVS) effectively models AGB of trees in freshwater forests, and a root:shoot ratio can be applied to estimate BGB, but the model does not account for greenhouse gasses or hydrology.

3.2. Carbon market requirements and implications

It is important for model developers to understand carbon market requirements to develop models that address the identified limitations, fully quantify net carbon sequestration, and are approved for application towards blue carbon project development. A discussion of carbon market requirements is provided as guidance to model developers.

Currently the carbon market is comprised of both compliance and voluntary emissions trading schemes. These emissions trading programs are collectively referred to as carbon markets. Carbon market standards and registries typically administer the programs and ensure the credibility of emission reduction projects. Examples of voluntary carbon market registries include the American Carbon Registry (ACR), the Climate Action Reserve (CAR), and the Verified Carbon Standard (VCS, a program of Verra). Methods to develop a carbon offset align with international standards (ISO 14,064–2) and are detailed in what is referred to as a carbon protocol or methodology depending on the offset registry (Sapkota and White 2020). These carbon market standards and registries have specific requirements for the use of models both at the overall standard level and at the more specific protocol or methodology level.

Protocols and methodologies typically undergo some combination of public consultation, peer review and stakeholder input to provide a transparent, rigorous scientific framework and accounting procedure for the development, verification, and monitoring of offset projects (Gillenwater et al. 2007). A protocol or methodology addresses each aspect of the project, such as eligibility criteria including temporal and spatial boundaries, baseline establishment, monitoring of emission sources, sinks and pools, QA/QC methods, risk accounting, and quantification of emission reductions, which pending verification become carbon offsets. The protocol becomes the foundation for third-party validation and verification in accordance with standardized and transparent market practices. Overall, the protocol works in concert with programmatic requirements set by the registry to ensure that credits issued will meet the underlying principles that offsets are real, "additional", quantifiable, verifiable, permanent and enforceable.

There are many commonalities across the multiple standards on the use of models for carbon project development. Generally, models must be specified or meet eligibility criteria in an approved protocol or methodology in order to be applied by a carbon project developer. In addition, the outputs of the model must align with the parameters and equations of a given methodology to be applied. Therefore, models need to be developed in concert with carbon market and methodological requirements. Currently, the most viable protocols for blue carbon are within ACR and VCS. Below are requirements of models for ACR and VCS methodologies.

For ACR, process-based biogeochemical models and empirical models may be approved for use under specific ACR-approved AFOLU methodologies to quantify emissions (ACR 2020). To be applicable, a model must have the potential to model emissions from the relevant practice change(s) with consideration of relevant factors; have been accepted in a peer reviewed scientific publication and/or been published by a government agency; and allow for the calculation of uncertainty in predicted emissions. ACR may also approve other models on a case-by-case basis via an ACR-lead peer review process. ACR has a list of factors that must be considered, where relevant such as atmospheric factors (i.e., nitrogen concentration in rainfall), daily meteorology, soil conditions, hydrology, etc. (ACR 2020).

ACR also requires that there be a study or studies that demonstrate that the use of the selected model is appropriate for the relevant IPCC climactic region in which the project is situated. The IPCC AFOLU 2006 guidelines note that an appropriate model should be capable of representing the relevant management practices and that the model inputs (i.e., driving variables) are validated from country- or region-specific locations that are representative of the variability of climate, soil, and management systems in the country (ACR 2020). Where a project consists of multiple sites, the model must be validated for at least 50% of the total project area relevant to the restoration practice where the project area covers up to 50,000 ha; or at least 75% of the total project area where the project area relevant to the restoration practice covers more than 50,000 ha. In addition, the area for which the model is validated generates at least two-thirds of the total project emission reductions (ACR 2020). One methodology within ACR added further requirements that models must also be parameterized, calibrated and validated for a specific scenario, project type, and area, and should preferably use at least 2 years of ecosystem flux data .[3]

With respect to the use of models under VCS, the use of models must be specified in the methodology applied by a project. All of the current VCS blue carbon methodologies allow for models to be used in place of field measurements to estimate certain parameters (e.g., soil organic carbon or expected submergence in the baseline scenario) (VCS 2019). No methodologies are necessarily built around a specific model although the MEM model is referred to in one wetland methodology (VCS 2019). VCS requires that models be publicly available from a reputable and

[3] https://americancarbonregistry.org/carbon-accounting/standards-methodologies/restoration-of-california-deltaic-and-coastal-wetlands

recognized source such as the IPCC or government agency; parameters chosen based on studies by appropriately qualified experts; reviewed and tested by an appropriate organization or an appropriate peer review group; have comprehensive and appropriate requirements for estimating uncertainty; be calibrated by parameters such as geographic location and local climate data, and use conservative assumptions and parameters that are likely to underestimate GHG emission reductions or removals. These criteria, however, are targeted at more complex models and may not be necessary for simpler models. Some VCS methodologies have specific requirements such as validating models with direct measurements from a proxy area that exceed the general VCS requirements.

Though measurement approaches for ACR and VCS are broadly similar, there are differences that can affect the cost of model development and on-the-ground monitoring of projects. The VCS methodologies allow the use of several notable default factors for the calculation of emissions. Default values for CH_4 are offered for areas with mean salinities >18 ppt and >20 ppt. Default values for N_2O are offered for areas with mean salinities between 5 ppt and 18 ppt, and for when they are >18 ppt, with values given for both open water and wetland sites. Also, sites in Louisiana can use default factors for N_2O emissions in fresh to saline habitats that are not receiving nutrient inputs.

For both ACR and VCS, existing methodologies may go through a revision process to modify a methodology to account for the use of a model or entirely new methodologies may be developed to apply models and advanced technologies such as artificial intelligence (AI), machine learning (ML) and remote sensing (RS) such as lidar. These emerging technologies show potential to facilitate the scaling up, cost-effectiveness, and accuracy of MRV. For instance, machine learning, remote sensing, and scientific modeling may help improve the accuracy of accounting for net sequestration in wetlands and reduce burdensome on-the-ground monitoring and large monitoring uncertainties that make many blue carbon projects cost-prohibitive (Brown et al., 2005; Heuvelink et al., 2020; Lloyd et al., 2013). However, it remains uncertain whether these technologies may ever be entirely relied upon without additional or complementary ground-truthing due to the complexity of wetland ecosystem data required for MRV. This will also require scientific knowledge gaps to be addressed, which based on our review of the scientific literature for the Mississippi Delta include: 1) baseline CH_4 and N_2O emissions from fresh, brackish, and saltwater emergent wetlands; 2) soil sequestration and N_2O emission rates for wetlands receiving hydrologic restoration; and 3) CH_4 emissions and soil and tree sequestration rates of wetlands impacted by sediment diversions. To address barriers preventing blue carbon project development adoption, user-friendly and publicly available wetland models need to be developed that are in sync with carbon market protocols to reduce uncertainty deductions and facilitate MRV. Ultimately, enhancing methods of MRV are key to ensuring the integrity and scalability of wetland carbon credits that maximize co-benefits to society.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Sarah Mack reports financial support was provided by Kosmos Energy.

Data availability

Data will be made available on request.

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